

# Diffuse-like recommender with enhanced similarity of objects

YA-HUI AN<sup>1</sup>, QIANG DONG<sup>12</sup>, CHONG-JING SUN<sup>2</sup>, DA-CHENG NIE<sup>1</sup> and YAN FU<sup>12</sup>

<sup>1</sup> *College of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China*

<sup>2</sup> *Big Data Research Center, University of Electronic Science and Technology of China, Chengdu 611731, China*

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**Abstract** – In last decades, diversity and accuracy have been regarded as two essential measures in evaluating recommender systems. However, a clear concern is that a model focusing excessively on one measure will put the other one at risk, which means that it is not easy to greatly improve diversity and accuracy simultaneously. In this paper, we propose a method which can be used in many being diffuse-like algorithms, like ProbS, BHC and HHP, to get more relevant and personalized recommendation results on user-object bipartite networks. The main idea is to enhance the RA similarity of objects in the transfer equations, by giving a tuneable exponent on the shoulder of RA similarity, to intentionally regulate the resource allocation on objects of different degrees. Experiments on three benchmark data sets, MovieLens, Netflix, and RYM show that the modified algorithms can yield remarkable performance improvement compared with the original models.

**Introduction.** – Nowadays, the explosive growth of storage capability has allowed people to collect and store almost all the information generated every day. This so-called “big data” provides great benefit to our life, e.g., we can easily get the cast list of a niche film via search engines. However, we also find that it becomes very difficult to find the relevant movie of our interest from countless candidates, if we cannot describe it by appropriate keywords. On this *information overload* occasion, *recommender systems* arise to help us make the right decisions.

Different from search engines requiring keywords, recommender systems are designed to uncover users’ potential preferences and interests based on users’ past activities and profile descriptions, and accordingly deliver a personalized list of recommended objects to every user. In the last decade, recommender systems have become a significant issue in both academic and industrial communities. The early recommender models are based on a simple observation that similar users are likely to purchase the same items, or, the items collected by the same user are prone to be similar to each other, such as collaborate filtering and content-based methods. These methods are shown to give accurate recommendation results, but they also confront a recommender system with the risk that more and more users will be exposed to a narrowing band of popular items, leading to poor diversity among users’ recommendation lists [9, 12].

Given this, many other recommendation models have been proposed in the literature, including dimensionality reduction techniques [1, 13–15], diffuse-like methods [2, 16, 19], social filtering [17, 18], and hybrid recommendation models [1, 11, 19]. However, people found that accuracy and diversity seem to be two sides of the seesaw: when one side rises, the other side falls. Examples are two primary diffuse-like methods, ProbS [2] and HeatS [3], which mimic two basic physical processes on user-object bipartite networks. ProbS is demonstrated to give recommendation results with good accuracy but poor diversity, while HeatS is found to be effective in providing a diverse recommendation lists at the cost of accuracy.

This diversity-accuracy dilemma has received considerable research attentions in the field of recommender systems. Zhou et al. [1] designed delicately a nonlinear hybrid model of HeatS and ProbS, called HHP, which achieves significant improvements in both accuracy and diversity of recommendation results. Another two effective methods modified respectively from original ProbS and HeatS, named Preferential Diffusion (PD) [5] and Biased Heat Conduction (BHC) [4], also make a good trade off on accuracy and diversity. In addition, [19] also proposed a balance diffusion(BD) algorithm, which is performed better than the above three typical methods both in accuracy and diversity.

In the first diffuse-like model ProbS, every user distributes the total resource he receives previously from objects, back averagely to his neighbor objects. The niche objects will receive lower final resources (recommendation scores) because they have fewer neighbor users (resource portals), thus rank in the bottom of the recommendation lists. That is why ProbS suffers from poor diversity. In view of this, the PD model proposed by Lv et al. [5] intentionally allocates more resource to small-degree objects, and less resource to large-degree objects. For the resource of a given user, every neighbor object receives the percentage approximately inversely proportional to its degree. Compared with ProbS, PD simultaneously improves the diversity and accuracy of recommendation results.

With the similar motivation, we proposed a method which can be used in many being diffuse-like algorithms, like ProbS, BHC and HHP, to get better recommendation results on user-object bipartite networks. we propose to enhance the RA similarity in the transfer equations of diffuse-like models, by giving a tuneable exponent on the shoulder of RA similarity, and traverse this parameter to achieve the optimal recommendation results. Experiments on three benchmark data sets, MovieLens, Netflix, and RYM (Rate Your Music) show that our model can yield a great performance improvement compared with the original models.

**Data sets.** – Three read-world data sets are adopted to test the recommendation result, namely, MovieLens, Netflix and RYM (Rate Your Music). Here we will briefly describe these three data sets. MovieLens, a movie rating data set, was collected by the GroupLens Research Project at the University of Minnesota and can be found at the website [www.grouplens.org](http://www.grouplens.org). Netflix, a randomly sampled subset of the huge data set provided by the Netflix company for the Netflix Prize ([www.netflixprize.com](http://www.netflixprize.com)) [6]. RYM, a music rating data set, is obtained by downloading publicly available data from the music ratings website [www.RateYourMusic.com](http://www.RateYourMusic.com) [1]. In this paper, we make use of nothing but the binary information whether there exists an interaction between a user and an object in the past. The basic statistics of the three data sets are presented in Table.1.

To evaluate the performance of different models, each data set is randomly divided into two subsets: the training set  $E^T$  containing 90% of the links and the probe set  $E^P$  with 10% of the links. The training set is treated as known information to make recommendation and the probe set is only used to test the relevance of the recommendation results.

**Methods.** – In this paper, a recommender system is represented by a bipartite network  $G(U, O, E)$ , where  $U = \{u_1, u_2, \dots, u_m\}$ ,  $O = \{o_1, o_2, \dots, o_n\}$  and  $E = \{e_1, e_2, \dots, e_q\}$  correspond to  $m$  users,  $n$  objects and  $q$  edges between users and objects, respectively. This bipartite network could be fully described by an adjacency matrix  $A = \{a_{l\alpha}\}_{m \times n}$ , where the element  $a_{l\alpha} = 1$  if there exists an edge between user  $u_l$  and object  $o_\alpha$  (user  $u_l$  collects

Table 1: The basic statistics of three data sets, where  $n$ ,  $m$  and  $q$  denote the number of users, objects and edges, respectively;  $\langle k_u \rangle$  and  $\langle k_o \rangle$  are the average degrees of users and objects.

Data set	$n$	$m$	$q$	$\langle k_u \rangle$	$\langle k_o \rangle$
MovieLens	943	1,682	100,000	106	59.5
Netflix	10,000	5,640	701,947	70.2	124.5
RYM	33,762	5,267	675,817	20	128.3

object  $o_\alpha$ ), meaning that user  $u_l$  declared explicitly his preference on object  $o_\alpha$  in the past, and  $a_{l\alpha} = 0$  otherwise. For every target user, the essential task of a recommender system becomes to recommend him a sublist of uncollected objects of his potential interest.

Most diffuse-like recommendation models work by assigning every object  $o_\alpha$  an initial level of resource  $f_\alpha$ , where the resources on all the objects constitute a resource vector  $\mathbf{f}$ ; then the resources will be redistributed among objects according to the formula  $\mathbf{f}' = W\mathbf{f}$ , which reads

$$\begin{pmatrix} f'_1 \\ f'_2 \\ \dots \\ f'_n \end{pmatrix} = \begin{pmatrix} w_{11} & w_{12} & \dots & w_{1n} \\ w_{21} & w_{22} & \dots & w_{2n} \\ \dots & \dots & \dots & \dots \\ w_{n1} & w_{n2} & \dots & w_{nn} \end{pmatrix} \begin{pmatrix} f_1 \\ f_2 \\ \dots \\ f_n \end{pmatrix} \quad (1)$$

where  $W_{n \times n}$  is the resource transfer matrix.

Analogous to mass diffuse process in user-object bipartite network, Zhou et al. proposed the Probabilistic Spreading (ProbS) model [2], also referred to as Network-Based Inference (NBI). For a target user  $u_l$ , the initial resource vector  $\mathbf{f}$  is defined as  $f_\alpha = a_{l\alpha}$ , where  $a_{l\alpha} = 1$  if user  $u_l$  has collected object  $o_\alpha$ , otherwise  $a_{l\alpha} = 0$ . The transfer equation  $w_{\alpha\beta}$  in matrix  $W$  is written as

$$w_{\alpha\beta}^{\text{ProbS}} = \frac{1}{k_{o\beta}} \sum_{l=1}^m \frac{a_{l\alpha} a_{l\beta}}{k_{u_l}}, \quad (2)$$

where  $k_{o\beta} = \sum_{i=1}^m a_{i\beta}$  and  $k_{u_l} = \sum_{r=1}^n a_{lr}$  denote the degrees of object  $o_\beta$  and user  $u_l$ , respectively.

Another diffuse-like model mimicking the heat-spreading process is called HeatS [?]. The initial resource vector  $\mathbf{f}$  of HeatS is the same as that of ProbS. The key difference between ProbS and HeatS is the resource redistribution strategy: ProbS works by equally distributing the resource of each node to all of its nearest neighbors, the overall resource remains unchanged; while in HeatS every node absorbs equal proportion of resource from every nearest neighbor, the overall resource increases in the process. Specifically, the difference of HeatS from ProbS lies in the transfer matrix  $W$ , which is described as:

$$w_{\alpha\beta}^{\text{HeatS}} = \frac{1}{k_{o\alpha}} \sum_{l=1}^m \frac{a_{l\alpha} a_{l\beta}}{k_{u_l}}, \quad (3)$$

As we mentioned before, ProbS enjoys high recommendation accuracy yet low diversity, while HeatS designed specifically to address the challenge of diversity suffers from terrible accuracy. Many researchers attempted to solve this diversity-accuracy dilemma and have found out some effective ways. For example, a *hybrid* model of HeatS and ProbS, named HHP, was proposed, with a tunable parameter  $\lambda$  in the transfer equation  $w_{\alpha\beta}$ :

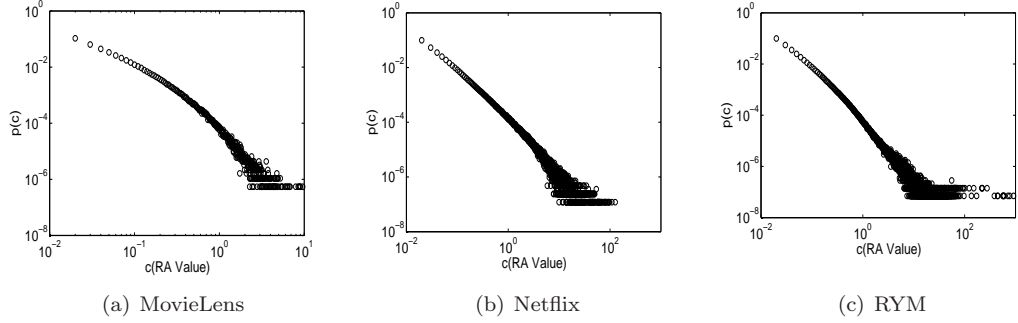


Fig. 1: The power-law distribution of RA values on three different data sets.

$$w_{\alpha\beta}^{\text{HHP}} = \frac{1}{k_{o_\alpha}^{1-\lambda} k_{o_\beta}^\lambda} \sum_{l=1}^m \frac{a_{l\alpha} a_{l\beta}}{k_{u_l}}, \quad (4)$$

It is easily observed that HHP reduces to ProbS when  $\lambda = 1$ , and HeatS when  $\lambda = 0$ .

**Empirical results.** — For most of aforementioned diffuse-like methods, the summation formula  $\sum_{l=1}^m \frac{a_{l\alpha} a_{l\beta}}{k_{u_l}}$  is a common component of the transfer equations. Zhou et al. [10] defined this summation formula as the **Resource-allocation (RA)** index, which is regarded as a significant similarity measure of two objects because it considers not only the number of common users but also the degrees of these common users. Fig.1 shows the distributions of RA index on three data sets. It is clear that the distributions follow almost quasi-power-law, which indicates that the RA similarities of most pairs of objects are weak and the RA value ranges a large scope (see Table.2). For the user-object bipartite network, the RA similarity can not effectively distinguishes the similarity of objects in an appropriate scale.

In Fig.2, we plot the heat map of **RA** similarity against degrees of arbitrary pair of objects on three data sets (Fig.2(a), Fig.2(c), Fig.2(e)). the darker is the color, the bigger is the **RA** similarity of two objects. We find that a majority of RA values are very low, especially for the pairs of small-degree objects, which validates again the heavy-tailed distribution of RA values.

Note that the RA index is a key factor in measuring the resource transfer between objects. Based on above empirical results, we infer that a few large-degree objects receive much resource (recommending opportunity), while a majority of small-degree objects get little resource, thus are seldom recommended. What is more, two popular objects are likely to be bought by the same users, which does not mean these two objects are similar to each other. On the contrary, two niche objects bought by the same users may have high similarity. Thus, the recommendation performance may be improved if we modify the RA index to intentionally increase (decrease) the similarities of large-degree (small-degree) objects. Specifically, the negative effect of quasi-power-law distribution of RA values will

Table 2: The minimum and maximum values of RA index on three data sets.

Data set	minRA	maxRA	magnification
MovieLens	0.0015	9.60	$6.4 \times 10^3$
Netflix	0.0010	126.5862	$1.2 \times 10^5$
RYM	0.00058	912.8531	$1.57 \times 10^6$

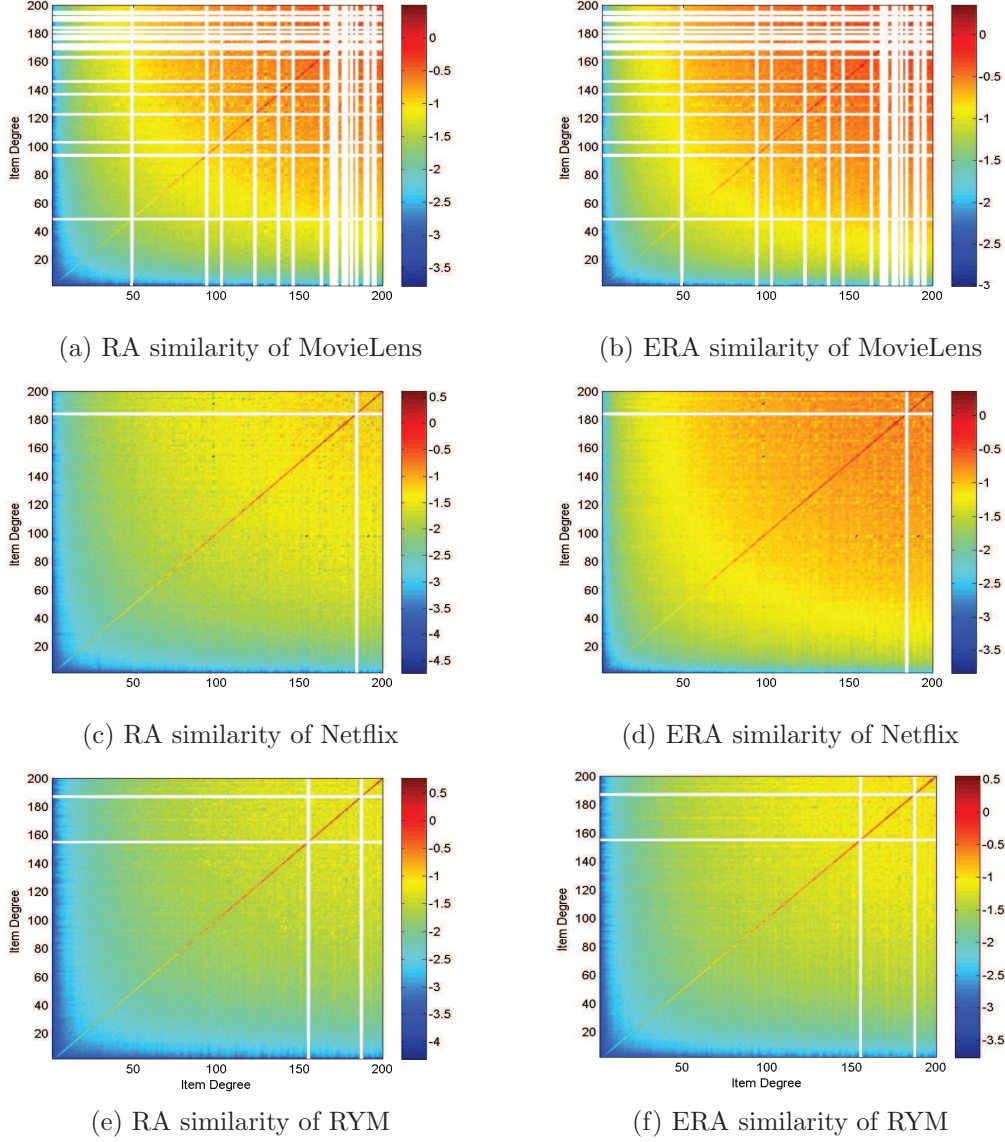


Fig. 2: The heat map of RA similarity against degrees of arbitrary pair of objects on three data sets.

be weakened by giving an exponent  $\sigma < 1$  on the shoulder of RA index, named **Enhanced Resource Allocation (ERA)** index:

$$s_{\alpha\beta}^{\text{ERA}} = \left( \sum_{l=1}^m \frac{a_{l\alpha} a_{l\beta}}{k_{u_l}} \right)^{\sigma}, \quad (5)$$

By replacing the **RA** index in transfer equations with our parameterized **ERA** index, we can modify most diffuse-like recommendation models on user-object bipartite networks, expecting an improvement on both accuracy and diversity. For **ProbS** model, the resource that object  $\alpha$  obtains from objects collected by the target user  $i$  can be written as:

$$f_{i\alpha}^{\text{ERA-ProbS}} = \sum_{\beta=1}^n \frac{a_{i\beta} s_{\alpha\beta}^{\text{ERA}}}{k_{\beta}}, \quad (6)$$

**Metrics.** – In order to evaluate the relevance of recommendation results, we adopt three typical metrics in this paper. In recommender systems, *accuracy* is the most important aspect in evaluating the recommendation performance. A good algorithm is expected to give accurate recommendations, namely stronger ability to find what the users like. We make use of ranking score  $RS$  [4] and precision enhancement  $ep(L)$  [1] to measure the recommendation accuracy. For a target user, the recommender system will return a ranking list of all his uncollected objects to him. For a link between user  $u_i$  and object  $o_{\alpha}$  in probe set, we compute the rank ( $RS_{i\alpha}$ ) of object  $o_{\alpha}$  in the recommendation list of user  $u_i$ .

$$RS_{i\alpha} = \frac{p_{\alpha}}{l_i} \quad (7)$$

In the above definition, object  $\alpha$  is ranked in the  $p_{\alpha}$ -th position of the recommendation list of user  $i$ , and  $l_i = n - k_i^T$  is the number of objects in recommendation list of user  $i$ , where  $k_i^T$  is the degree of user  $i$  in the training set  $E^T$ . The ranking score  $RS$  of the whole system can be obtained by averaging the ranking score values over all user-object links in the probe set, written as:

$$RS = \frac{1}{|E_P|} \sum_{(i,\alpha) \in E_P} RS_{i\alpha} \quad (8)$$

In practice, we will focus on the top-ranked objects rather than checking the whole recommendation list. Thus, a more practical approach is to check the top  $L$  objects recommended to the target user to calculate how many objects are recommended correctly. *Precision* is the mostly used metric defined in this way. However, for a sparse data sets the precision may be very low, but for a dense data set it may be high. Obviously, finding a better way to avoid bringing some bad effects from data sets themselves is necessary. Zhou et al. [1] introduced enhanced precision  $ep(L)$  which considers improvement compared with the precision of random recommendations. A random recommendation will randomly choose  $L$  objects from the train set and recommend them to the target user, where  $L$  is the length of the recommendation list.

$$ep(L) = \frac{1}{m^P} \sum_{l=1}^{m^P} \frac{n_l}{L} \times \frac{n^T - k_l^T}{k_l^P} \quad (9)$$

where  $m^P$  is the number of users in the probe set,  $L$  is the length of recommendation list,  $n_l$  is the number of relevant objects in the recommendation list of user  $u_l$ ,  $n^T$  is the number of objects in the train set,  $n^T - k_l^T$  is the number of uncollected objects of user  $l$  in the train sets, and  $k_l^P$  is the degree of user  $u_l$  in probe set.

Besides accuracy, diversity is taken into account as another important aspect to evaluate the recommendation results. We make use of Hamming Distance ( $h(L)$  for short) to measure the recommendation diversity. The Hamming Distance between user  $i$  and  $j$  can be described as:



$$h_{ij}(L) = 1 - \frac{q_{ij}(L)}{L} \quad (10)$$

where  $q_{ij}$  is the number of common objects in the top  $L$  positions of both lists of user  $i$  and user  $j$ . Averaging  $h_{ij}(L)$  over all pairs of users with at least one link in the probe set, we obtain the hamming distance  $h(L)$  of the whole system, where greater value means better personalization of users' recommendation lists.

**Results.** — By adjusting the parameter  $\sigma$  to appropriate values, we get the heat map of ERA similarities against the degrees of objects on three datasets (Fig.2), where  $\sigma = 0.7$  for MovieLens(Fig.2(b)),  $\sigma = 0.6$  for Netflix(Fig.2(d)) and  $\sigma = 0.8$  for RYM(Fig.2(f)). Compared with Fig.2(a), Fig.2(c) and Fig.2(e) respectively, we find that the similarities of many pairs of objects are increased from RA index to ERA index, reflected by larger area of darker color in the figure.

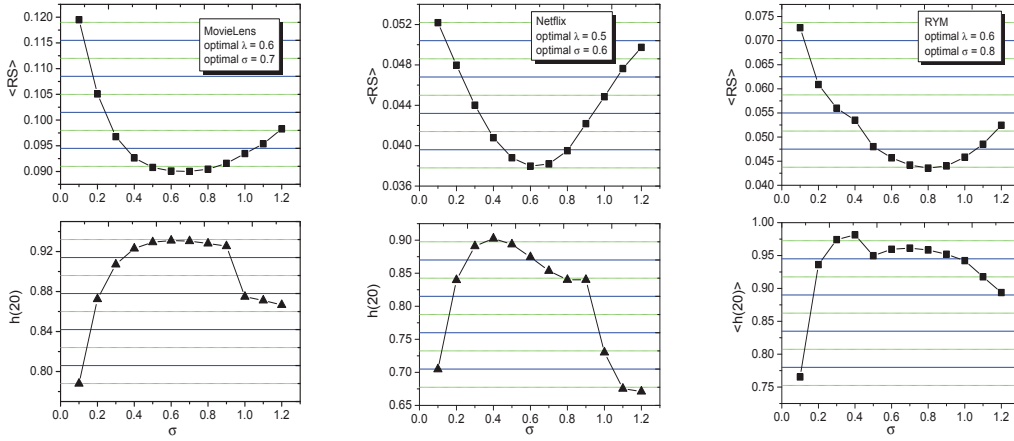


Fig. 3: The changes of ranking score and hamming distance when traversing parameter  $\sigma$ , where  $\lambda$  is tuned to be optimal for every  $\sigma$  value.

By replacing RA with ERA index in the transfer equation of HHP model, we get the enhanced HHP (HHP+ for short) model. Fig.3 plots the values of two typical measures, ranking score and hamming distance, when parameter  $\sigma$  is traversed from 0.1 to 1.2, where the other parameter  $\lambda$  is tuned to be the optimal value for the corresponding  $\sigma$ . We can see that in a large range of  $\sigma < 1$ , the ranking score value is smaller than that of  $\sigma = 1$  for three data sets, which means that the accuracy of HHP+ model will be better than original HHP if  $\sigma$  is tuned delicately.

Specifically, the ranking score reaches its optimal value when  $\sigma = 0.7$ ,  $\sigma = 0.6$ , and  $\sigma = 0.8$  for MovieLens, Netflix and RYM, respectively. Table.3 summarizes the detailed statistics of recommending results for HHP and HHP+ models on three data sets. We can see all the three metrics of HHP+ are improved compared with HHP. Especially, the ranking scores of HHP+ are decreased 3.14%, 15.23% and 3.78% than HHP on MovieLens, Netflix, and RYM, respectively. In a word, HHP+ outperform HHP on all the measures in three data sets, especially on Netflix.

We further investigate the effect of ERA on ProbS and HeatS. Table.4 shows the percentage improvement of three metrics by enhancing the RA similarities in three diffuse-like models ProbS, HeatS, and HHP. It can be clearly observed that the performance of ERA similarity are quite different on different models. For ProbS, who is widely known as an

accuracy-favoring method, the enhanced similarity brings an improvement on all the metrics on *MovieLens* and *Netflix* data sets, but has notable effect on *RYM*. For HeatS, who is famous for its extremely high diversity and terrible accuracy, the improvements of accuracy metrics on three data sets are remarkable. However, the diversity of HeatS is decreased compared with HeatS+, but still better than *HHP+* and *ProbS*. The optimal  $\sigma$  values of ProbS+ and HHP+ are all between 0 and 1, while for HeatS+ it lies on  $\sigma > 1$ , which means that the optimal  $\sigma$  values depends on the data set itself.

**Conclusion and Remarks.** – An important challenge of recommender systems is how to accurately recommend the unpopular objects in the absence of enough profile information, without degradation of recommendation accuracy of popular objects. In this paper, we proposed to enhance the RA similarity in diffuse-like recommendation models to improve simultaneously both of accuracy and diversity. Experimental results demonstrated the effectiveness of this modification on ProbS, HeatS and HHP on three typical data sets. Different from the quasi-power-law distribution of original RA similarity, the distribution of ERA similarity is more even, thus the similarity of a large proportion pairs of unpopular objects are increased, while the similarity of a few popular objects remains almost unchanged. That is why the proposed method greatly reinforces the existed diffuse-like models.

Although our method can improve the recommendation results, we still lack of a full understanding of the effect from the point of view of network topology, e.g., why the method can achieve significant improvement on HHP and HeatS but no remarkable effects on ProbS. Since the transfer equation  $w_{\alpha\beta}$  consists of another components besides RA (ERA) similarity, the influences of these factors should not be neglected.

Generally speaking, our work can be analogously applied to any similarity-based recommender models. We believe the current work will shed a light on the research on influence of network topology on recommendation results.

Table 3: The recommendation performance of **HHP** and **HHP+** models on three data sets.

Data	Methods	$\sigma_{opt}$	$\lambda_{opt}$	$RS$	$ep(20)$	$h(20)$
MovieLens	HHP		0.86	0.0923	26.33	0.9027
	HHP+	0.7	0.58	<b>0.0894</b>	<b>27.95</b>	<b>0.9187</b>
Netflix	HHP		0.83	0.04471	84.89	0.7559
	HHP+	0.6	0.51	<b>0.0379</b>	<b>90.09</b>	<b>0.8866</b>
RYM	HHP		0.76	0.04557	119.2	0.9369
	HHP+	0.8	0.59	<b>0.0435</b>	<b>123.70</b>	<b>0.9552</b>

Table 4: The percentage improvement of metrics by introducing ERA in ProbS, HeatS and HHP on three data sets.

Methods	DataSets	$\sigma_{opt}$	$RS$	$ep(20)$	$h(20)$
ProbS+	MovieLens	0.4	3.24%	3.3%	4.9%
	Netflix	0.5	3.32%	0.7%	12.45%
	RYM	0.8	0.61%	-1.6%	0.61%
HeatS+	MovieLens	1.1	30.1%	331.1%	3.43%
	Netflix	1.2	51.2%	>>100%	-10.3%
	RYM	1.1	17.6%	26.4%	0%
HHP+	MovieLens	0.7	3.14%	6.15%	1.8%
	Netflix	0.6	15.23%	6.13%	17.3%
	RYM	0.8	4.5%	3.78%	1.95%



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